Royapoor M, Antony A, Roskilly T.

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Energy and Buildings 2018, 158, 453-465.

DOI link to article:

https://doi.org/10.1016/j.enbuild.2017.10.022

Date deposited:

05/10/2017

Energy and Buildings 158 (2018) 453–465

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Review

A review of building climate and plant controls, and a survey of industry perspectives

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ARTICLE INFO

Article history:
Received 25 May 2017
Received in revised form 1 September 2017
Accepted 4 October 2017
Available online 13 October 2017

Keywords:
Building control systems
Renewable energy control

ABSTRACT

A historic and current perspective is offered of building climate and plant control techniques while also reporting the results of a survey that reveals more conventional control methods to still be preferred by industry-based practitioners. Specifically Artificial Neural Network and reinforcement and machine learning have seldom been taken up in practice by HVAC and BAS industries due to uncertainty, long training periods, and complexity in setting up and maintaining the system. Future buildings are expected to be responsive to other civic activities, namely power generation, storage and distribution and potentially even transport. Given that HVAC industry predominantly continues to deploy conventional techniques, future control solutions seem inevitably to be pioneered by the digital and information technology innovators. Conventional techniques such as PID and simpler computational methods which require no data-training are reported to continue to exist particularly on closed loop mechanical systems (hydronic or air-based) at plant level. Survey participants state that at and beyond building level, control and integration require software-intensive solutions to enable online data analytics, system and occupant feedback, diagnostics, renewable energy management but most urgently smart grid controls and forecasting. Most of these innovations are expected to come from sectors beyond the building automation industry.

Contents

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https://doi.org/10.1016/j.enbuild.2017.10.022

Nomenclature

AI	Artificial intelligence
ANN	Artificial neural network
BAS	Building automation system
BIM	Building information modeling
BMS	Building management system
CAV	Constant air volume
DALI	Digital addressable lighting interface
DDC	Direct digital control
GA	Genetic algorithm
FL	Fuzzy logic
HVAC	Heating, ventilation and air conditioning
IEA	International energy agency
MPC	Model predictive control
MPPT	Maximum power point tracking
PID	Proportional, integral and derivative
PIR	Passive infra-Red
PMA	Power management algorithm
PMV	Predicted mean vote
ppm	Parts per million
PSO	Particle swarm optimisation
RFID	Radio frequency identification
RL	Reinforcement learning
VAV	Variable air volume
WSN	Wireless sensor network
WWW	World wide web

1. Introduction

Holistic control of buildings is a multi-dimensional endeavour. It requires control mechanisms that can provide acceptable levels of comfort for the occupants, while also minimising the energy use and most importantly perform robustly under a variety of fluctuating conditions. The frequently conflicting nature of energy conservation and the delivery (or sustaining) of human comfort also makes optimisation techniques necessary in order to guide the system to the best possible compromise, with forecasting also imposing another inevitable layer of complexity.

Building performance is widely reported in terms of annual energy footprint per unit area (kWh/m^2 per year) [1]. Updates of EU rules (also implemented in UK building regulations) asks for the examination of buildings in terms of their carbon footprints (kg CO2/(m^2 year) [2]. Energy conservation in its simplest practice can therefore be defined as minimising CO2 emissions. Occupant satisfaction however is more convoluted to define and achieve. Despite expecting our buildings to perform better continually, building design remains dominated by static control parameters, whereby at early stages of design (and with little knowledge of the building in operation) a number of control parameter sets are decided by the architect and engineers [3]. Intelligent controls have the potential to address disadvantages of sub-optimally controlled buildings by collecting information from sensors to 'learn' what a building might require rather than relying on pre-determined set-points and standard assumptions [4].

Controls are categorised by component (i.e. HVAC, shading), parameter (i.e. temperature, RH, PIR, CO2), mode (manual, on/off, hybrid) and algorithm (PID, ANN) [5]. A significant efficiency benefit emerges from integration and automation of all controls in industries such as aviation, modern automotive or petro-chemical processes. Few individual examples exist on full building automation and if such an approach yields efficiency and occupant satisfaction. This work seeks to offer an overall review of building control techniques by examining the historic and current state of controls, and highlighting the strengths of some of the emerging computational methods, including control types that propose to use human comfort indices and pervasive sensing. Finally, the most promising future methods of building controls are identified and their strengths and weaknesses outlined. In order to examine real world adoption of both the emerging control techniques and recent methods that have moved beyond the prove of concept stage, a survey is undertaken of control design professionals working within building automation industry to explore views of industry-based control designers and the adaptation rate and success of advanced control methods proposed by the research community.

2. Building control strategies

Buildings experience a variety of internal and external disturbances, and the manifestation of these disturbances are most pronounced in the thermal domain. The primary role of controls has therefore been to regulate the thermal environment [6].

All controls essentially attempt to lessen the dependence on human experience and judgement, and to achieve (or optimise) one or a number of objectives according to certain criteria [7]. Every building envelopes one or a number of internal thermal zones with diverse degrees of service requirements. At any given time there are various control mechanisms acting at several different levels within most buildings. The following sections provide an overview of these different levels of controls.

2.1. Controls at field level

Designing an effective control entails breaking the overall process into smaller sub-systems each delivering a part of the process. Buildings are no exception, be it a simple control mechanism for a small dwelling to those in heavily engineered buildings that facilitate complex activities. Salsbury, T.I [8] divides the HVAC controls into three main subsystems:

1 Central plants (i.e. boilers, chillers and cooling towers) that generate cooling or heating.
2 Air, water or refrigerant-based distribution system (air handling units, hydronic systems) comprising of many components configured to deliver constant or variable air volume (CAV or VAV) or heating and cooling fluids to the conditioned zone.
3 Terminal units, for instance VAV dampers or a thermostatic valve.

Terminal units are mostly controlled by a local-loop operating either a modulating or switched mechanism. Central plants (as well as modulating terminals) predominantly employ proportional–integral–derivative (PID) controllers, with derivative action often disabled (as it responds aggressively to small changes). Historically the low-cost nature of building industry meant that systems were set up with a minimum number of sensors; with data collected and fed-back at long intervals. This of course wouldn't have presented a major problem because of the sluggish nature of response in buildings. Nonetheless this approach doesn't lend itself to more advanced controls or diagnostics. One other problem arising from inadequate sensor deployment is that a badly performing loop in a building is difficult to detect and re-tune as other loops might compensate for it. In reality problems such as offsets, oscillatory and sub-optimal control performances are generally tolerated in buildings because of the non-critical nature of space conditioning (compared for instance to chemical process, aviation or defence applications).

Research community has made considerable efforts to address the nonlinear and time variant nature of HVAC plants, in particular the issue of efficiency penalties at lower loads. Mathematical modelling of plants are the main test-bed for HVAC control strategies although since theoretical modelling carries major limitations, further work has also been done on empirical model fitting to assist dynamic model analysis, though results of such studies tend to be problem-specific [9]. Developments in modular simulation programmes have addressed problem-specificity; yet again the remaining challenge is that these programs describe the plant components in steady-state or quasi-steady-state modes [10,11]. This makes them suitable and computationally efficient for low frequency dynamic analysis but unsuitable for high frequency disturbances which are essential in solving control problems.

Apart from the changing behaviour of HVAC plants with load variation, at any given load there are numerous opportunities for optimisation of the system. For instance increasing cooling tower fan speed means more power consumption by fans, but it reduces condenser load by delivering cooler inlet water to the condenser, similarly higher chilled water flow temperature means lower evaporator energy use but higher pumping duties as the building cooling demand will require greater chilled water flow [12]. The situation is further complicated when several chillers are to be sequentially controlled to run at optimum points. Therefore ultimately a ‘global’ optimisation is required which makes computational interventions necessary.

2.2. Controls at management level

Traditionally the human operator would supervise all aspects of a building’s operational needs. Few organisations had any form of energy target or monitoring and ultimately 1973′s oil crisis gave birth to energy management as a separate discipline; with 1979s oil crisis making it imperative for governments and industries. 80 s and 90 s were however the key periods for building energy management systems (now referred to as BMS). Evolving from early, cumbersome and expensive systems, it was ultimately the falling cost of PCs and on-board plant intelligence that created the leaner and advanced systems that are available today. Increasing building complexity has also gradually brought more controllable elements under building ‘automation’ systems [13]. In addition to the conventional HVAC plants, modern buildings can contain active facades (i.e. smart glass, shading systems, automated windows etc.) and/or local generation (i.e. solar collectors, fuel cells, CHP etc.). Reports exist that suggests advanced building materials, aided by the science of human-computer interaction can turn building envelopes into dynamic and energy efficient climate moderators, as well as having the ability to interact with the building occupant [14]. The most important component of building management is however human comfort, which is not a static parameter, but it changes and the rate of change of comfort in a building is different from the rate of change of external factors [15]. Therefore it is possible that future building automation and communication networks will integrate a broad range of functions including access and security, fire systems, transport (i.e. lifts) and renewable supervision. Modern standards (such as BS EN ISO 50001:2011) also increasingly call for integrated building automation systems [16]; a demand that is supported by research efforts which show notable operational advantages when automation and integration strategies are in place [7,17,18]. The falling costs of data processing and storage capacity will also mean that control devices will be able to execute substantially more complex control algorithms. An additional benefit will be that intelligent buildings can perform functions geared more towards analysis and diagnostics than mere controls [8].

2.3. Control types

For brevity, and in order to maintain relevance, the control methods that are deployed currently in buildings are discussed, including earlier generation classic controls, current techniques and more prominent computational methods that have attracted most research activity.

2.3.1. Classic controls

2.3.1.1. Binary. Where no output modulation is sought, binary or on/off control has widely been used for small systems in buildings, in particular for temperature control via thermostats. Characterised by two switching points and a dead band in between; this mechanism is prone to hysteresis and overshoots [19]. In its basic form, binary temperature control also produces a deviation from set point that requires more sophisticated controls to rectify. One solution could be to use a switching algorithm such as pulse-width-modulation to generate a pulse train. This approach can be taken further to include both pulse width and pulse frequency modulation which is easier to set up for the practitioners [20].

2.3.1.2. Proportional–Integral–Derivative (PID). P, PI and PID are used for modulating continuous controls; therefore clearly only applicable to plants whose output is capable of modulating. Although developed as early as 1910 for ship and aeroplane automation, remarkably still 90% of industrial controls continue to use them [21]. Proportional (P) controller simply corrects the error by multiplying the deviation from the set point by a constant that is proportional to the magnitude of error. P controllers suffer from sustained offsets (persistent error between the set-point and prevailing value) that can only be rectified by the introduction of integral (I) action. Integral further adjusts the control signal by including the integral of error with respect to time, so as long as an error exists, the integral controller will continue to adjust the signal. Adding integral action clears the offset, but it could slow the system down and also reduce stability. Differential (D) action is therefore added to further complement PI because it corrects the low frequency errors accumulated by integrator action. Differentiators act on rapidly changing error values and ignore the slow changing values (i.e. they act on the ‘rate of change of error’, hence only rapid errors activate them). Derivative controls are however hardly used for the control of building plants. It’s worth noting that P controllers are also used in isolation with either I or D components (PI or PD controls). Quite understandably, to get the best out of a PID control system, various settings and constants (i.e. gains) need to be selected judiciously. The problem however is the non-linearity of all HVAC systems; whereby the system can be set up to work to perfection in one part of the operational range (i.e. full load) but responds badly at others (i.e. part load). The research community has proposed several auto-tuning techniques; for instance relay-auto-tuning [22], open loop step tests [23] or a combination of these [24]. A number of building automation companies offer products that incorporate these ideas [8]. Adaptive algorithms are another solution which are covered later.

The wide (and continuing) application of PID has sustained the development of many PID tuning techniques and associated soft and hardware packages [18]. Academic research into PID has however entered a state of diminishing returns and the trends move into the integration of PID with computational control methods to improve stability and response time [25–27].

2.3.2. Computational controls

The research community has been active in proposing replacements for classic controls by including some hybrid solutions that retain elements of classic controls. This sub-section outlines some of the most notable methods.

2.3.2.1. Supervisory method. Supervisory control was developed for industrial automation in late 1990s, and because of its potentials it provided the impetus for scientific research to broaden its application [28]. Over the past two decades, the collection of large volumes of on-line operational data, together with growing integration of BAS software has enabled the development of supervisory (and optimal) control strategies. In its most comprehensive form, this approach can find the optimal solution (operational mode/set point) for a system equipped with energy storage (thermal and electrical) while also taking into account the carbon and monetary costs of electricity and gas [29]. It is important to note that supervisory method encompasses a variety of techniques often involving training methods (Such as artificial neural networks, fuzzy logic or genetic algorithms). Supervisory controls are subcategorised into the following forms:

2.3.2.1.1. Model-free method. Supervisory control systems could either utilise a model of the targeted system (i.e. model based) or be model-free; where expert systems and on-line learning techniques are applied to guide the system to its optimal point, or allow the process to function optimally. Although each version can take several forms, supervisory control essentially suits complex control problems where operating points need to be updated constantly to find the most optimal under changing conditions. Model free supervisory control (also referred to as expert system) utilises knowledge harvested from online data streams to determine the optimum settings for system operation; therefore in essence it attempts to mimic the behaviour of a human operator and as a result, it can even work with 'incomplete' data sets (although an accuracy penalty ensues). One particular example of model-free supervisory controls is reinforcement learning (RL) technique; where the control system tries to improve its behaviour as a result of previous actions. Although reinforcement learning requires no prior knowledge of the system, at times the learning process could be unacceptably long, making them still impossible to implement in practice [30].

2.3.2.1.2. Model-based method. Model-based supervisory control takes the optimisation to a more advanced level by both selecting the set-point and 'predicting' the optimum time for a set-point change. An illustration of this could be a dynamic model of both space and chilled ceiling plant that was successfully developed within Hong Kong Polytechnic University. A supervisory algorithm was used to self-tune the set points every 10 min to achieve both comfort condition and energy efficiency [31]. Quite clearly this method is suited to more complex systems where updating operating points can yield higher efficiencies. Central chiller plants are particularly suited to this application. A similar study utilised simplified models of major central chiller components with genetic algorithm. The virtual system achieved cooling energy reduction of 0.73%–2.55% [32]. Essential to the success of model-based supervisory method is system models with simplified structures, high prediction accuracy, easy calibration and low computational costs [29]. A demonstration of this was made where an optimal model defined by several operational constraints was developed to control room heating. The model is then solved by an optimisation technique in real time, using dynamic programing and on-line simulation. The system included a weather predictor that formed temperature and solar irradiance forecast from 12 h to 1 day. This approach was put to test in a 'solar room', where high thermal capacity concrete floors were deployed to absorb and store solar energy. An underfloor heating system complemented solar heat. The results showed energy savings of 10–27% [33].

Supervisory control could also be a hybrid of model-free and model based techniques, as well as being based on other approaches such as performance map data, artificial-neural-network (ANN) or empirical-relationship. A detailed breakdown of these methods is provided by S. Wang & Z. Ma [29] that concludes the hybrid supervisory control method to suite practical applications best, as detailed model-based methods are not computationally efficient.

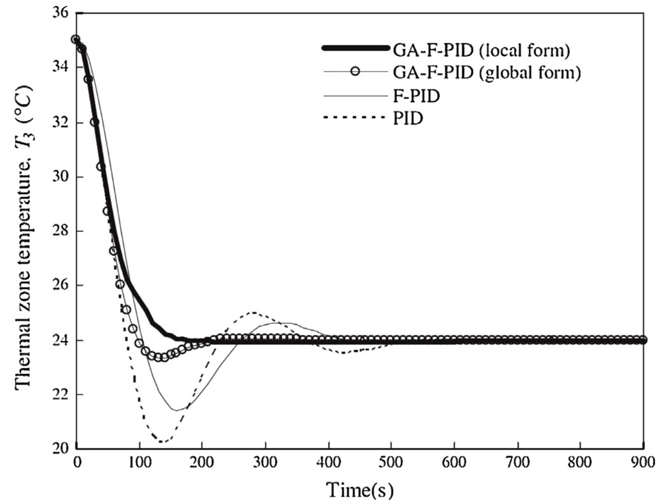


Fig. 1. Comparison of transient thermal zone temperature response for PID, F-PID, and global and local form GA–F-PID controllers (reproduced from [43]).

2.3.2.2. Reinforcement learning (RL). Initial control policies generated to oversee the operation of a complex building could prove suboptimal as the building moves through different phases of its life. RL tools can provide a solution by enabling self-calibration of control parameters; and in more advanced forms have been applied in conjunction with ANN or Fuzzy logics [34].

RL however continues to suffer from a long training process. The learning parameters and the dimensionality of the state and action space can also combine to hinders the ability of RL controller to find the right policies [30]. RL continues to feature more widely in neuro (and computer) sciences as opposed to applications in building controls [35]. The most recent efforts are limited to employing RL to tune a supervisory control which overlooks a building energy system, and to develop optimal controls for passive and active building thermal storage inventories [30,36–41]. RL however remains distinctly under-reported in building control literature.

2.3.2.3. Fuzzy logic (FL) controls. FL resembles human thought process in that it is capable of dealing with partial truth (conventional binary variable sets are either true or false). Consequently FL is capable of working with uncertainties in multivariant control systems more effectively. Except for the earliest attempts [42] FL controls are rarely used on their own for building control applications. Most successful applications entail the integration of FL with PID, ANN or other adaptive techniques [43]. FL has the same scope of application as PID where reportedly its application helped visual and thermal comfort and natural ventilation to be improved [44–47]. Where comfort expectations of building occupant change as a function of time, control systems could be coupled with pervasive sensing strategy so that a building learns to adapt to new preferences or new occupants. Reports show notable results when FL was applied to control energy and comfort in buildings [48,49]. Hybrid methods – where FL is combined with other techniques-have also shown great promise. Fig. 1 is a simulation-based comparison in performance improvement when first FL is used to schedule the PID controller gain coefficient (i.e. F-PID), and later genetic algorithm (GA) is introduced as a means to optimise the efficiency of a dynamic energy system (i.e. GA-F-PID) [43]. The latter achieves the best stability control with practically no oscillation or overshoot.

FL is widely used in industrial automation and also HVAC controls [50]. However applications of higher level FL controller for energy and comfort optimisation in 'real buildings' is missing.

2.3.2.4. Robust controls. HVAC plants are selected for the maximum load they need to serve, although for most of their working life they will be operating at part loads; sometimes with severe efficiency penalties and control problems. Robust control aims to address this problem by algorithms that deliver disturbance attenuation and stable operation across the full operational range [9,51]. H–∞ optimisation synthesis has proven successful in constructing robust controllers where a reference signal is asymptotically tracked [52], however this technique require plant and space uncertainty definition to form fixed (or variable) parameters and also contains high-order mathematics, that can make them difficult to implement from a numerical point of view.

2.3.2.5. Artificial neural networks (ANN). The research community has used the learning ability of ANN to chart the relationship between input and output data aiming for initially the prediction (of behaviour) and ultimately optimised control of systems. Examples of recent simulation-based attempts include the adaption of ANN to control a double skin façade [53], hybrid ground source heat pump operation [54] and building energy and comfort optimisation [55–57]. Within all these attempts the ANN carries out predictions that are used to decide the next control action. Another work has reported improvements greater than 50% in the efficiency of HVAC systems, when ANN are used to develop 'predictive controls' for thermal management and comfort [58].

2.3.2.6. Agent-based controls. Agents (in the form of electronic devices) have been deployed and stationed strategically mostly in process automation and electronic engineering allowing control flexibility and robustness. These are interacting, automatous and flexible components that have found widespread applications in extremely complex systems [59–61]. The large, dynamic and the multi-faceted nature of buildings mean that vast amounts of information is unfolding within and beyond the envelope continuously and building scientists have deployed agents-orientated methods to perform a variety of different tasks (coordination, switching, simulation and reporting) to enable comfort and energy management. Building-specific applications include developing agent-based management systems with particle swarm optimization (PSO); a method inspired by collective movements observed in birds and fish [62,63] in order to optimise complex non-linear control problems. One such (simulation based) study reports energy and comfort improvements over different operating scenarios [64]. Similar works found agent-based controls able to deal with energy shortage while achieving comfort levels, as well as managing to optimise HVAC performance that included a VAV system [65,66]. An additional feature of these systems is their open architecture that could enable retro-fitting into existing BAS to facilitate greater functionalities [67]. Autonomous agent based controls however, understandably steer the system towards a more decentralised decision making model that makes it more difficult to predict the overall system behaviour. An area of active research is merging and integrating agents' interplay to produce desirable 'system-wide' behaviour. However with the exception of a few industrial process (and manufacturing line) control prototype demonstrations, real world performance of agent based systems, either in real buildings or even controlled laboratory condition is not yet available.

2.3.3. Summary

In practice a large degree of overlap exists between different techniques outlined above. A comprehensive control strategy ought to offer robustness, efficiency and adaptability. As a result most promising efforts involve a number of artificial intelligence and optimisation techniques. For instance on-line Reinforcement Learning (RL) was used in a study to 'tune' a supervisory controller. The RL uses prior knowledge of the system generated by off-line fuzzy rule simulation and using the training process it also begins to correct erroneous off-line information [41]. This was reported to offer a much quicker training process of only a year to enable controlling a complex low-energy building system.

As more building elements are now automated, controls increasingly need to perform a supervisory role to enable much more difficult tasks; such as optimising energy and comfort while supervising generation, export and storage. Such central approach is only possible through computational methods and task integration which is also promoted by standards such as BS EN ISO 50001:2001. Although the building control industry has adapted some of the simpler approaches to automation and optimal scheduling, more complex approaches such as ANN are not adapted because of the difficulties in guaranteeing convergence, robustness, requirement for additional parameter specification, increased set-up time and computationally demanding operations for the typically low cost building controls. The control design industry has also become used to the strengths (and understands the weaknesses) of PID; and this partly explains the reluctance to experiment with alternatives.

3. Emerging trends

Integration of renewable energy is increasingly making buildings into generators as well as consumers of energy, with the need to control the intermittency of such small scale generation. In addition more complex comfort driven controls assisted by digital technology, online data and PC-based sampling tools have created greater need for finding global optimums using computational methods. This section covers notable emerging trends in more details.

3.1. Renewable integration

Increasingly older building stocks with conventional HVAC installations are retrofitted with renewable forms of energy conversion to improve their sustainability credentials. This trend however necessitates stability management of power grids, regulating and scheduling loads corresponding to the consumption as well as optimising operating costs. Renewables are inherently dynamic; thereby capturing, integrating and controlling the flow of such multi-vector energy sources is challenging. There has been various energy management control methods that deploy different algorithms for integrating renewables into existing systems either on or off grid.

These energy management systems (EMS) handle a complex multi-carrier management system (i.e. containing electrical, thermal and mechanical components) by supervising and running the same system for obtaining the desired long term results [68]. Optimal integration of one or more renewable sources into an existing system is a moderating exercise given the erratic nature of renewable sources, the costs of storage along with the assimilation of new control decisions over a time period [69]. For example, solar power depends widely on the insolation which can vary due to cloud cover, while wind power is a function of wind speed and susceptible to seasonal changes. When renewable energy is available the power generated can either be utilised immediately or stored (with storage quite often an expensive option with efficiency or conversion losses). Given that conventional fuels have to provide back up during periods of inadequate renewable generation, power forecasting, location-specific optimisation, sizing and specifying renewable sources all become necessary parameter inputs of controls. Linear-programming, genetic algorithm, differential evolution, neural network, Model Predictive Control (MPC), PID and fuzzy logic have all been used to integrate renewable systems off-grid (i.e. standalone mode).

Current forecasting research employs models such as Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), regression trees, Numerical Weather Prediction (NWP) and ANN to predict wind speed and power [70]. For solar power prediction the most accurate regression models are Least Median Square (LMS), MLP, and SVM [71]. Genetic algorithm(GA), SVM, and ANN were used for data prediction of hydro energy [72]. The control system can then use these predictions to make decisions on supply and demand. Where location data is available general methods can be used to match PV array design to site requirements, and ANN models can be used where such data is unavailable as suggested by Mellit et al. which allows designers to change the number of modules and storage capacity according to the demand with a maximum error of only 6% [73].

GA remains behind a wide range of integration and management of renewable-based hybrid energy systems as it provides a mathematically efficient local optimum. Hernadeza et al. [74] used GA to generate the sizing of PV plants and used multi-objective method for optimisation of the entire system. Similarly Yokoyama et al. [75] used multi-objective optimal unit sizing for integrating PV and wind energy systems. Seeling-Hochmuth [76] coded five decision making vector variables over the course of the annual year using GA while Senjyua et al. [77] proposed the use of GA for optimising controls of diesel generators, PV, wind turbines and batteries and reported that the hybrid system was 10% more efficient than a conventional system without renewables.

Neural networks similarly bring flexibility, parallel processing and learning ability to renewable controls. Fuzzy logic has if-then statements that can balance power and energy according to requirements, and it is mainly used for multi-input, multi-objective system control when inputs are highly variable or unstable and where it provides more stable outcomes than a regular PID. A hybrid control method comprising of neuro-fuzzy logic was developed by Azadeh et al. to optimise the solar system operation at any location [78]. A Maximum Power Point Tracking (MPPT) method was also reported to have been used in PV systems in recent years by researchers and the industry alike where intelligent tracking systems utilise the weather data to predict maximum power from the sun and align the PV system to generate maximum power. The classic fuzzy logic was also considered to be used in conjunction with Perturb and Observe (P&O) algorithm in order to design PV with MPPT system utilising previous data and knowledge of the system [79]. Perera et al. studied the application of Pareto multi-objective system to integrate solar and wind energy systems with an internal combustion generator (ICG) and argues that integration of renewable energy technologies is more eco-friendly and economical for stand-alone systems but is best at higher capacity hybrid systems to resolve intermittency issues [80]. Abedi et al. proposed a power management system to integrate PV, wind turbine, diesel generator, hydrogen fuel cell and battery using a differential algorithm and fuzzy logic multi-objective technique. In this model, Power Management Algorithm (PMA) takes the information of the power system of PV, wind and other renewable sources to manage the voltage and current settings to the optimal level while using information on the state of charge of the battery. The author also noted that this system can be effectively used for any combination of stand-alone hybrid energy systems [81].

Supervisory control and data acquisition (SCADA) is the most common form of industrial control and data acquisition system which offers distributed autonomous supervisory control capacity that allows the integration of renewable systems across a wide area. It uses a human-machine interface with input and output devices, controllers and software that networks the data online. The working principle is based on supervisory control at three different levels. The first level of supervisory control is done to achieve a total optimisation, the second level co-ordinates regional optimisation and functional co-ordination and the final level is designed to achieve autonomous and automatic control at a higher speed and frequency. The necessary information is collected and delivered to the controller which also raises an alarm in case of any critical failure after diagnostics analysis. All the start and stop signal decisions for the power and voltage settings are recorded in the EMS [82]. SCADA has been used for district level smart renewable energy systems [83]. Spectrum Power SCADA has been used in transmission grid applications using service-oriented architecture [84]. Building Energy Management Systems are already in place that control, manage and monitor all technical services in a building using sensors, variable speed drives, valves and actuators with microprocessors converting analogue to digital data [85]. In these systems field measurements can be accessed from an online server through any registered device and the remote control access of power flow and voltage is enabled via the Transmission Control Protocol/Internet Protocol (TCP/IP) Ethernet cloud. These systems achieve integration by Direct Digital Control Systems. This method measures data, then processes the data against background or baseline information and finally initiates a control action. The sensor data is measured and given to the controller which uses a set point to generate a PID-based output signal and controls values, actuators, pumps, etc. Increasingly, hybrid energy systems with renewable contribution require software-intensive intelligent energy management system (IEMS) where power discontinuity can be reduced by switching on and off between various sources and backups. For example, PV can use MPPT with a charge controller, if one source cannot provide the required output, it can be fulfilled by other sources while storing surplus power generation. Such solutions are available by some commercial system designers in the form of integrated energy supply and storage controls. They are mainly used for saving power and energy while monitoring and controlling energy usage of various appliances. For instance marketplace proprietary products exist now where the controls have the ability to switch appliances on and off to take advantage of any available solar electricity or heat within a system that also includes heat pump technology and battery storage [86] to boost solar enabled energy autonomy from 30% to 80% with the same array capacity thanks to battery integration and dynamic controls.

3.2. WSN, web service and diagnostics

Wireless sensor networks (WSNs) provide low powered energy efficient solutions for building extensive yet non-invasive networks within commercial and domestic buildings. These enable low cost and at the same time detailed monitoring of the indoor environment [3,15]. WSNs have improved significantly in terms of bandwidth, reliability and cost effectiveness; and are now widely adapted in areas such as aviation, automotive, agriculture, security and defence. However building application of such technologies has remained limited. WSN technology shows great promise for mapping and controlling energy flow in buildings, and the industry has moved towards the standardisation of communication protocols [87]. Transmission and interference challenges associated with WSNs are for the most part solved and further standardisation is underway to support greater adaption of them in the industry [88]. The network demand of WSNs could be embedded with various internet protocols. Open Protocol web services emerged in commerce in 90 s (with BACnet and LON as forerunners) and with its increasing popularity, web-based solutions have now completely dominated BAS systems. Beyond HVAC, WSNs allow other information such as weather and occupant/operator data and process information to be integrated into the automation system [89].

In addition to mapping energy, WSN can enable occupancy detection, light and noise surveys and temperature profiling. A recent study successfully deployed WSN to demonstrate a surprising 10 K temperature range across air intakes of data racks within a data centre [90]. Real world monitoring data of this nature can enable better design and configuration of HVAC services and building layouts. Buildings with very stringent indoor climate control can particularly benefit from pervasive WSN deployment. Two separate studies for instance conducted continuous monitoring of the indoor air quality in both an art museum and a greenhouse to deliver a more precise climate control in these spaces [91,92]. WSN, together with web services can transform the BAS domain from an information island to a real-time and interactive web-based service. BAS in itself is predicted to feature more fault detection and isolation using web-enabled data analytics. This is a particularly important development for both energy efficiency and critical mission engineering. A demonstration of online diagnostic test (ODT) was successful detection of abrupt changes in HVAC process, even when they occur simultaneously [93,94]. Multiple stage faults, in particular when they happen simultaneously require more convoluted efforts to detect [95]. Similarly identifying slow degradation and gradual faults are still challenging [93]. Over the past few years the operating cost of buildings has risen dramatically (and continues to rise as a product of high fuel prices). This trend, together with the rapid pace of smart systems, will justify higher capital costs for technologies that can bring about lower operating costs though optimisation and diagnostics [96–98], and the synergy between WSN and Web service can allow auto-tuning and self-commissioning to become the norm [89,99].

3.3. Smart home and appliance level energy management

Current efforts to optimise building management is seeking to take the controls down to appliance level to address grid stability, renewables and storage management. For instance 'governable' building loads such as washing machine, water heater, electric vehicle, and air-conditioner are dynamically controlled using a demand response home energy management (HEM) system [100]. These loads are regulated according to the priority, comfort and pattern of customer usage. An HEM algorithm using demand response as the guide to the customer pattern has been used to determine the management of the appliances in order to reduce energy cost and consumption and thereby increase the efficiency while maintaining load stability. Smart home control and networks are also anticipated to offer improved efficiencies over conventional management systems. Murad et al. proposed a three layer system to eliminate data loss resulting from wired and wireless sensors [101]. The first layer manages the systems that handle all the interference from all the wireless networks. The second layer controls all light sources and household appliances and cuts off any unwanted demands from such interferences and the third layer controls the operating time of the electronic appliances. A study based on hybrid power system proposes the use of a hermite wavelet embedded Neuro-Fuzzy indirect adaptive method with an MPPT for the PV system and a Neuro-fuzzy indirect adaptive control for the SOFC (solid oxide fuel cell) which was simulated along with an electrolyzer, battery, micro-turbine, super-capacitor and a wind turbine for a domestic load [102]. Since there are a number of sub-systems, a supervisory control is suggested to regulate power flow. The PV and wind energy power outputs are monitored, with any excess first charging the battery and second supplied to the electrolyzer to generate hydrogen. When there is not enough power generated for the load, SOFC and the micro-turbine outputs are used to balance out power shortages. It was observed that the hermite wavelet improves control accuracy when compared to a PI controller especially in terms of undershoot steady-state errors, overshoots, and settling time as it processes data in small continuous modules. A conversion efficient system that works on fuzzy based MPPT under any weather conditions with the integration of genetic algorithm was used for a study of a standalone PV system without battery [103]. The results showed faster response time and minimum error when compared with conventional algorithms like P&O (Perturb and Observe), INC (incremental conductance) etc. Other notable examples include home energy management systems (HEMS) that are connected to household appliances and smart meters monitor, shift and shed the load to stay below a sanctioned power limit [104]. A Lyapunov optimization method was used to develop a simulated-based online smart home energy management system that reduced electricity cost while maintaining comfort levels for (theoretically) any number of users with or without user intervention [105]. An efficient ANN based prediction network was proposed by Moon et al. in order to offer occupancy based heating control [106].

Another study has emphasised the use of time-of-use (TOU) energy pricing models in their control algorithms for multiple users [107]. Any HEMS aims to reduce the operating and managing costs while increasing the comfort levels for the customer. The algorithm essentially creates a priority list from multiple users to select appliances that can be shifted or switched off during peak hours based on customer usage patterns and implement decisions in advance based on that priority list during off-peak hours. Fengyu et al. developed a dynamic tool to simulate and control the heating and cooling in a building using a model predictive control that managed energy consumption and user comfort levels [108].

Sun et al. conducted a control study of a residential building using a non-linear predictive energy management model on a PV system with battery storage [109]. This Model Predictive Controller (MPC) with a radial basis function network (RBF-NN) attempts to predict building load, battery status and PV output to reduce energy gaps in the building. Given perfect weather forecasts, the simulation-based results achieve between 96%–98% of the optimal performance. In another residential building study conducted by Randa et al. a PV, diesel generator and a battery system were governed by a demand side management control (DSM) algorithm which sought to maximise renewable energy utilisation [110]. The control algorithms also used data from controllable loads (Washing machine, heater, Iron, dish washer, vacuum cleaner) which have an operation time and non-controllable (Fridge, TV, Stereo, Lights, Desk-lamp, Computer) loads which are higher priority loads. Finally, a novel idea was introduced to reduce errors in local maximum power point (LMPP) and global maximum power point (GMPP) due to shading in PV systems which involves developing control algorithm that draws inspiration from the pattern of whale hunting optimization along with a differential evolution algorithm (WODE) in static and dynamic conditions [111]. It works to reduce any errors of algorithms like P&O as well as saving processing speed and storage needed for algorithms like ANN. The experiment results show that this method solves the errors due to shading as well as being able track GMPP five times faster than existing methods in either dynamic or steady state conditions.

3.4. Control strategies using occupancy detection

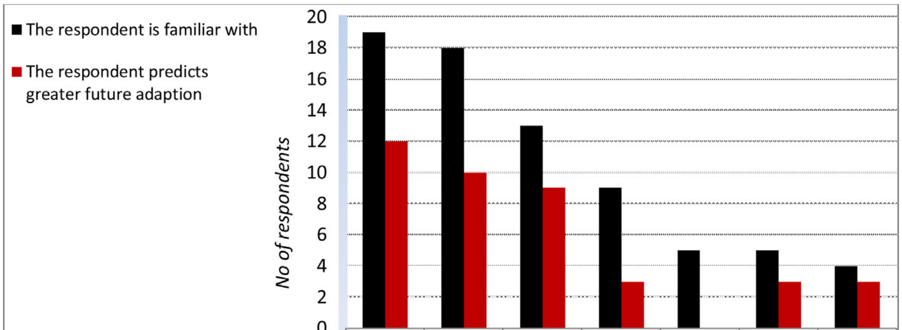
Buildings, particularly those intermittently occupied can benefit greatly from using occupancy data to inform controls. Demand or occupancy driven HVAC controls are now deployed in very simple forms in buildings (i.e. a pre-set CO2 concentration value triggers the ventilation boost). Research conducted in this area shows significant energy saving potentials, although downsides such as insufficient ventilation and high CO_2 concentration remain a possibility [112,113]. At the heart of this problem lies inadequate detection of occupant density despite the much improved levels of detection accuracy compared to earlier years. Occupant detection technologies that are currently deployed in buildings are divided into individualised and non-individualised systems, based on whether the individual in the sensing area is detected, tracked and identified or not [114]. PIR sensors are the most widely adapted but cannot detect the stationary occupant and are not able to identify or track a subject. To overcome this limitation, PIR sensors are coupled with other sensor types. A combination of PIR, acoustic and CO2 sensors were adapted by two research groups; where between three machine learning techniques that were applied, hidden Markov model proved the best, achieving an average detection accuracy of 73% [115,116]. Occupancy detection relying on CO2 level alone could be misleading as carbon dioxide could be a function of several different parameters. Occupancy detection accuracy of 89% was reported in a study where a combination of PIR, CO2 and a video camera were used and coupled with historical data [117]. A variety of techniques have also been developed for individualised occupancy detection; whereby the identity and coordinate of the occupant is determined by the sensing system [114]. Individualised detection enables a more refined regulation of HVAC system, and is most effective in open plan offices; but issues concerning privacy limits wider adaption. A study undertaken in Southern California University looked at radio frequency identification (RFID) technology to determine the real time occupancy level in order to control the HVAC systems [114]. This work required the building occupants to wear an active RFID tag throughout the study. System performance varied between different areas, and different mobility levels; with an average detection rate of 88% for stationary and 62% for mobile occupants at zone levels (the study involved 13 specified thermal zones). The overall detection rate across all zones was 100%. In other words the system was able to tell the total number of people at all times, and where exactly they were most of the time. Adjusting lighting and ventilation level in response to 'instantaneous' measurements have also been reported to improve energy efficiency [114,118–121]. Although using more convoluted methods to 'predict' short term occupancy levels (i.e. occupancy information within a Model Predictive Control (MPC)) hasn't produced significantly better results [122]. More recent attempts includes the use of Wi-Fi, digital calendars and also mobile phones to detect occupancy [123]. In contrast to occupancy-driven controls, the concept of control-orientated occupant's behaviour [124] exists where occupants operate control devices (windows, shades, fans etc.) to bring about desirable conditions with significant impact on building operational behaviour. Extensive empirical studies on occupant manipulation of their visual, thermal and acoustic environment has been conducted, leading in instances to stochastic algorithms, dynamic or otherwise, that describes this relationship [125–127]. In recognition of this a strong sense of conviction exists between researchers that regardless of the great promises of system automation, the occupants should ultimately remain capable of overruling to assure acceptability of controls system [128–130]. The most advanced occupancy detection capabilities now exists in digital and communication industries and social media platform owners. Mainstream media reports that social media platform owners can enable occupant headcount using mobile phones and in turn inform 'smart' building and city operations, but unresolved ethical issues exists while occupant and face recognition technologies continue to move at a much faster rate than the regulatory guidelines.

3.5. Control strategies using elements of human comfort

The norm in building climate management has been to set up the HVAC (or BAS) system so that it hunts a single fixed target temperatures to facilitate human comfort. Increasingly however researchers seek to move away from applying fixed temperature set points to working environments. This is primarily driven by the adaptive comfort principle which argues that if a climatic change produces discomfort, people react to restore their comfort [131–133]. These efforts have collectively informed European (and hence British) as well as American standards [134–136]. BS EN ISO 15251 (2007) subsequently defines an 'allowable' indoor operative temperature band, taking the form of a lower and upper value that could be defined daily or even hourly as a function of outdoor running mean temperature. These adaptive temperature bands are defined for 4 different building categories depending on operational sensitivity and occupant expectations [137]. Computational controls have enabled a large number of comfort-based studies where thermal comfort (i.e. Predicted Mean Vote (PMV)) is used to guide the controller [15,138]. In a more comprehensive approach, controls use both comfort and energy as indices to optimise building operation. P. Bermejo et al. designed an adaptive algorithm that used a fuzzy logic system; this enabled the control system to use 'on-line' learning to adjust a radiator's actuator. The system would learn the preference of an occupant in order to chase the most appropriate target temperature in the space; and in doing so minimised the number of direct adjustments made by the occupant. A similar study included air quality and energy indices in addition to PMV to set appropriate control set point of an HVAC systems [139]. To achieve this, a multi-objective optimisation controller was designed to determine optimal indoor air condition in real time (giving equal weighting to thermal comfort – indoor air quality and load reduction). Sensors would pass environmental conditions to a central controller; the readings were then compared to baseline values to send the correction signal to HVAC plant. The experiment reports a 17.5% reduction in cooling load at the same time as maintaining CO_2 concentration below 1000 ppm. Optimisation of combined human comfort and energy efficiency is only achieved through computer-based methods, and reinforcement learning (RL) technique is an example where positive results have been reposted by many [41,140–142]. Dalamagkidis and his team used RL to find the balance between energy and comfort however the learning process took 4 years and even after this period, the system would still make mistakes (i.e. calling for cooling in winter) [143,144]. Other researchers shortened the training process to one season by using template fuzzy rule and off-line knowledge of the plant [41].

3.6. BIM-enabled automation

Although initially developed as a means to compile and share data, building information modelling (BIM) is anticipated to enable virtual models to enable design at building concept stage to also facilitate detailed design and commissioning and fault detection; with the eventual integration into the building lifecycle. Interfacing with pervasive sensing, model based supervisory controls and fault detection and diagnostics (FDD) is also reported to be within reach [145]. This means that much of the innovation will need to happen at the interface between different disciplines (i.e. HVAC vs lighting controls) to allow fuller integration and that is fundamentally a software development issue. However the development of holistic, fully integrated controls for buildings (as in aircraft or robotics industries) is more challenging primarily due to time domain gap that can range from sub-seconds (i.e. communication systems) to years (i.e. geothermal heat sources) [146]. All-inclusive building automation are reported to offer substantial saving potentials [147,148] but have stayed limited to simulation efforts with no real world deployment noted so far [149–151]. Combining the controls of a daylight-linked lighting installation with a satisfactorily functioning HVAC system has been attempted [152,153] and remain one of a handful of full integration case-studies. The need to accommodate more renewables and micro-generation as well as the vision of internet of things, smart grids, smart homes and smart cities



	PID	Fuzzy logic	ANN	Supervisory method	Robust method	Agent Based	RL
The respondent is familiar with	19	18	13	9	5	5	4
The respondent predicts greater future adaption	12	10	9	3	0	3	3

Fig. 2. Industry views on familiarity with current and potentials of future control methods.

suggest the possibility of data-driven analytics enabling controls at various layers. However despite encouragement by international bodies such as IEA the case for integrated control of all building services is inadequately articulated and any benefits remain unclear.

3.7. Summary

Combining several control methods to address energy conservation and human comfort simultaneously forms the foundation of the most sophisticated research efforts. Pervasive WSN can transform BAS which currently is mainly a reporting tool to decision support, diagnostics and optimisation tool. Renewable integration and storage also require supervisory control methods. However given the difficulty in designing generic control systems fit for every type of renewable generation and storage integration, robust solutions involving prediction and decision making models continue to stay in research and demonstration stage. Successful detection of occupant to inform control action remains technically and ethically challenging while some oppose this in favour of control-oriented occupant behaviour (e.g. adaptive thermal comfort).

4. Survey results

Literature review suggests that the latest control tools developed by the scientific community can successfully govern uncertain systems (i.e. buildings) and offer substantial energy and comfort improvements. These improvements could be obtained with no fundamental changes to the building systems that are installed today. In order to engage the views of control designers in HVAC and building automation sectors, a questionnaire was developed and sent to 61 industry-based building control engineers in order to examine the industry's confidence in implementing proposed new control tools. Of a pool of 61, only 20 responses were generated (10 practitioners from Europe, 5 in USA, 2 in India, 2 in China and 1 in Malaysia) with one response lacking sufficient quality to include. The questionnaire listed seven control types outlined on Fig. 2 and asked the participants [1] which control methods they were familiar with, [2] which will be shaping future building controls and automation products, [3] if there is a unity of purpose in research and industry-led building control development [4] and finally invited them to share their perspectives and predictions on how building automation will evolve in future. Collectively the responses suggested that industry-based control developers had limited knowledge of the work of science community, in particular regarding more advanced computational methods covered in Section 2.3.2. A disparity of conviction also exists in that the participants expressed limited confidence on the potentials of advanced control techniques. Fig. 2 illustrates control methods that the participants were familiar with, and the methods that they regard as significant contributors to the future development of building automation:

Clearly PID is rated as the most familiar and also offering the highest potential even for future adaption. Individual statements suggest that PID is an aging technique but has been a constant and trusted engine behind commercial expansion and economic growth of controls industry and the backbone of most if not all simple or complex hydronic or air based systems installed today. The respondents also noted that either in isolation or combined with predictive models, it will continue to be integral to the future of building and HVAC controls. 3 participants however contested that in practice PID is often not set up properly by the commissioning or maintenance teams. The views expressed on the 6 remaining techniques indicates that the participants were progressively less familiar with these, and regarded them more suitable for industrial process controls than HVAC and building applications, where they have not been adequately tried and tested. All comments concerning knowledge of and interest in control techniques concerned PID, Fuzzy method and ANN mostly with ANN being regarded as having the ability to interpret complex data and offer an alternative to PID. It is also interesting to note that a correlation of 0.94 exists between methods that practitioners were familiar with, and those they regard as strong future contenders. Further views offered examples of specific companies and software products that use cloud computing, the internet of things and software ability to analyse historical data as the main drivers of future controls. 16 out of 19 responses noted that there was not a unified purpose between the industry and academia and lack of direct engagement, complexity and performance uncertainty was stated as the reason why controls industry has not adapted solutions developed by the science community. This was particularly clear since the participants used commercial products (and not scientific work) to point out future control contenders. The control practitioners also noted that clients prefer systems that are easy for the commissioning engineers to set up, and are able to offer robust control under all conditions, with data logging as the only additional request, while seldom wishing to install optimisation capabilities. It was also mentioned that renewable energy controls are often contracted out to the renewable specialist team, so while renewable data is often routed through BAS, an integrated control system for the building and for instance PV-T panels are not sought by clients. Further comments noted that integrating new control methods into legacy applications are difficult and manufacturers regard disruptive technologies as risky and expensive. Therefore scientific solutions and commercial products are not developing in a uniform manner which makes the prediction of technologies that are a part of future BAS and control landscape difficult.

In conclusion, the following are practical ways to bridge the gap between scientific research in advanced controls and commercial solution developments:

1. Policy and funding incentives to unite the work of science and industry, particularly by organisations with international reach (i.e. the EU commission).
2. More real-world lighthouse projects that demonstrates the efficiency and comfort benefits of advanced controls. University campuses can in particular use their own estates to move research-driven control methods beyond proof of concept.
3. Greater interdisciplinary works in particular with IT sector where the fastest pace of development exist compared to any other sector, in order to take advantage of WSN, online analytics and evolutionary techniques to facilitate better decision support tools.
4. Research work that can clarify whether complete automation (as is typical in aviation and automotive sectors) might be relevant in BAS industries, or if the diversity of occupant comfort preferences mean that occupied zone controls should be left out of advanced automations, and if so:
5. Further guidelines on the best building management philosophies that can facilitate:
   a. A complex control and optimisation strategy that allows the building to generate, manage and store energy and participate in a smart energy grid.
   b. Leaves the building occupant completely autonomous to interact with the space in order to adapt and restore their audio-visual and thermal comfort.

The following table summarises a historical perspective and ongoing trends reflected in the views of both the scientific and commercial sectors.

Table 1 Historical and future trends in building control.

Control domain	Classical periods	→	Modern buildings	→	Future trends
Management level	• *1950 + 60s: Human Operator* • *1970s: Initial computer-based management systems introduced, functionality limited to monitoring only.*	→	• *1990s: Open Protocol introduced (BACnet – LON . . .)* • *2000s: www begins to dominate BAS systems* • *2000s: Inter-operability + standardisation of protocols and SCADA.*	→	• *Single software platform for all controls, domestic too* • *Controls to approach real time* • *Buildings digitally connected (soft infrastructure) and responsive to wider energy network conditions* • *FDD and optimisation enabled via computational controls* • *Mobile Devices provide interface.*
Automation	• *1970s: Micro-chip analogue electronic control.*	→	• *1980s: Microprocessor panels (high density I/O)* • *1980s: Application-specific DDCs.*	→	• *Self-commissioning, auto-tuning and demand side controls will be the norm* • *Comfort-orientated voting.* • *Forecasting and AI-enabled HVAC to include buildings in smart grid systems*
• *Terminal level:* • *Room controls* • *Actuators + valves* • *Primary plants*	• *Manual operation* • *Local loop Pneumatic control systems (1950s)* • *PID (1950s onwards).*	→	• *Schedule driven, PIR, CO2 and daylight-linked room controls* • *PID continues* • *1990s: Fuzzy logic* • *2000s: Rapid expansion of wireless* • *2000s: computational controls (governing 'uncertain systems') stay within R&D.*	→	• *PID (self-tuning and coupled with dynamic models)* • *Live terminal operation to aid carbon and cost efficient management of buildings as energy storage and generation entities.*

5. Conclusions

The fragmented nature of the building industry means that simulation, control and optimisation tools are independently developed and often incompatible. Demonstrations of benefits of complete building control integration are limited to simulation-based efforts and the benefits of full automation (where for instance lighting and HVAC services are responsive to one another) remains unclear. Recent research views buildings as components of a wider interconnected energy infrastructure (i.e. Smart Grid) and has moved beyond building level to examine demand response and grid stability. Most components of classic control solutions (i.e. PID-controlled air or water loops) have reached design maturity with limited scope for improvement; while future building controls will need to supervise more renewables, local generation and most probably forms of energy storage which points to more advanced computational techniques (i.e. ANN or agent-based) that have so far largely remained in demonstration stage. BAS industry survey results point to a reluctance to adapt what is regarded as riskier alternatives and therefore PID (with occasional higher level heuristic supervisory or model based control) continue to dominate the building plant systems that are installed today; while simultaneously the research community is seeking to control building energy systems to be responsive to fluctuations in gas and electricity networks. It is possible that some of the computational control strategies that were covered in this work will only be adapted in isolation, limited capacity or be abandoned altogether in preference for emerging digital solutions that can control a building in responsive mode to wider energy systems. Digital technologies and cyber space are now the foremost incubators for innovation at a rate that outperforms most other fields of science. Cheap, multi-functional sensors, together with widespread deployment of sub-meters that produce vast quantity of fine-grained data are inevitable components of multi-vector controls required in responsive buildings of the future. Building owners need to make operational choices that are only possible by multi-objective and near real-time control methods based on forecasting, on-line analytics and knowledge of the system condition at and beyond the building level. While BAS industry's classic control methods will continue to be deployed particularly in closed loop mechanical HVAC systems, research needs are shifting towards the interface between these and the wider energy infrastructure where software intensive solutions within a data-rich environment is expected to offer near real-time control of hybrid energy and storage networks. In parallel human comfort scientists prefer less automation in occupied zone in favour of the occupant's ability to adapt to restore their audio-visual and thermal comfort. New guidelines are required at and beyond building levels to define how building control architecture can allow complex, evolutionary and responsive building services management while also maintaining occupant autonomy, and how buildings can act dynamically to enable grid stability and energy management at city levels.

Acknowledgements

The authors would like to thank Engineering and Physical Sciences Research Council (EPSRC) for their financial support which enabled the undertaking of this work (EPSRC grant reference EP/I000755/1).

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